ground water

Hybrid-Optimization Algorithm for the Management of a Conjunctive-Use Project and Well Field Design

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Abstract

Hi-Desert Water District (HDWD), the primary water-management agency in the Warren Groundwater Basin, California, plans to construct a waste water treatment plant to reduce future septic-tank effluent from reaching the groundwater system. The treated waste water will be reclaimed by recharging the groundwater basin via recharge ponds as part of a larger conjunctive-use strategy. HDWD wishes to identify the least-cost conjunctive-use strategies for managing imported surface water, reclaimed water, and local groundwater. As formulated, the mixed-integer nonlinear programming (MINLP) groundwater-management problem seeks to minimize water-delivery costs subject to constraints including potential locations of the new pumping wells, California State regulations, groundwater-level constraints, water-supply demand, available imported water, and pump/recharge capacities. In this study, a hybrid-optimization algorithm, which couples a genetic algorithm and successive-linear programming, is developed to solve the MINLP problem. The algorithm was tested by comparing results to the enumerative solution for a simplified version of the HDWD groundwater-management problem. The results indicate that the hybrid-optimization algorithm can identify the global optimum. The hybrid-optimization algorithm is then applied to solve a complex groundwater-management problem. Sensitivity analyses were also performed to assess the impact of varying the new recharge pond orientation, varying the mixing ratio of reclaimed water and pumped water, and varying the amount of imported water available. The developed conjunctive management model can provide HDWD water managers with information that will improve their ability to manage their surface water, reclaimed water, and groundwater resources.

Introduction

Hi-Desert Water District (HDWD), the primary water-management agency in the Warren groundwater subbasin, California (Figure 1), plans to construct a waste water treatment plant to reduce future septic-tank effluent from reaching the groundwater system. The treated waste water will be reclaimed by recharging the groundwater basin via recharge ponds as part of a larger conjunctive-use strategy. HDWD wishes to identify the least-cost conjunctive-use strategies that control groundwater levels, meet California State regulations, meet water-supply demand, and identify the optimal locations of new pumping wells. The aquifer is modeled as unconfined and the decision variables are the locations of the new pumping wells and the optimal pumping/recharge operating

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schedules; therefore, the management problem is formulated as a mixed-integer nonlinear programming (MINLP) problem. Nonlinearities arise from the nonlinear nature of an unconfined aquifer and the integer-programming problem arises from the identification of optimal new pumping well locations.

Optimization-management models have been developed to manage groundwater resource systems for more than two decades. The design of optimal-groundwater management systems may involve determining the values of continuous decision variables, such as extraction and injection rates from wells, and the values of discrete decision variables, such as well locations. The objective function is usually formulated to minimize the operation cost within the management-planning horizon. The management model is subject to state and decision-variable constraints, for example, desired groundwater levels, meeting water-supply demands, and maximum pumping capacities.

Groundwater-management models are a class of modeling techniques in which simulation models of groundwater systems are incorporated into an optimization formulation, and have been shown to be powerful and useful methods to solve design and operation problems associated with groundwater hydraulic control, water supply, and remediation. There exists a large body of literature related to the application of traditional optimization methods to solve groundwater-management problems. Linear programming (LP; Molz and Bell 1977; Lefkoff and Gorelick 1986), nonlinear programming (NLP; Ahlfeld et al. 1988; Wang and Ahlfeld 1994; McKinney and Lin 1995), and dynamic programming (Chang et al. 1992; Culver and Shoemaker 1992, 1997; Willis 1979) have been combined with the groundwater-flow model (or coupled groundwater/mass-transport models) to identify optimal-operation policies. Gorelick (1983), Yeh (1992), Wagner (1995), Ahlfeld and Mulligan (2000), and Mayer et al. (2002) have presented extensive review papers on optimization-management models. Among these methods, the successive linear programming (SLP) algorithm has been shown to be a useful tool for solving nonlinear groundwater-management problems, and the optimal solution converged rapidly. Nishikawa (1998) and Ahlfeld and Baro-Montes (2008) used the SLP algorithm to solve groundwater-flow management problems; the problem solved by Nishikawa (1998) had nonlinear boundary conditions and the problem solved by Ahlfeld and Baro-Montes (2008) was an unconfined groundwater-flow problem.

When well locations are considered in the nonlinear groundwater-management problem, the result is a MINLP problem because of the discrete nature of the decision variable. Several methods are available for solving the general MINLP. These include the branch-and-bound method (Fletcher 1987), outer approximation/equality relaxation method (Duran and Grossman 1986; Kocis and Grossman 1987), generalized Benders' decomposition (Watkins and McKinney 1998), and approximate MINLP method (McKinney and Lin 1995). All of these methods rely on gradient-based techniques. However, groundwater-management problems are often characterized as nonconvex, nonlinear-programming problems (Willis and Yeh 1987), relying only on conventional gradient-based search methods to solve the MINLP problems is usually infeasible. These methods cannot address the discontinuity caused by the integer decision variables, and the optimal solution easily can be trapped in a local optimum because of the nonlinearity and there is no guarantee that a global optimum will be found. Hence, global-search techniques (non-gradient-based optimization algorithms), such as the genetic algorithm, simulated annealing, and tabu search have been extensively applied to the problems of groundwater management (Dougherty and Marryott 1991; McKinney and Lin 1994; Huang and Mayer 1997; Aly and Peralta 1999; Zheng and Wang 1999; Mantoglou et al. 2004; Park and Aral 2004; Hsiao and Chang 2005). Although global optimization schemes can identify the global optimum, the convergence is very slow when the number of decision variables is large.

In this paper, a hybrid-optimization algorithm that couples a genetic algorithm (GA) with a SLP algorithm is developed to solve the MINLP problem. The MINLP problem is decomposed into two parts, integer (or binary) and real parts. The integer part is solved using the GA. Using the optimal integer decision variables from the GA, the MINLP problem is simplified to the NLP problem, which is solved using a SLP algorithm. We demonstrate that the hybrid-optimization algorithm has the capability to solve a MINLP problem for a conjunctive-use management and well-field design problem by using the algorithm to determine the least-cost conjunctive-use strategies for HDWD, referred to as the case study. The results of the case study are then evaluated with a sensitivity analysis. The sensitivity analysis evaluates three alternatives: (1) new pond orientation, (2) required percentage of reclaimed water, and (3) availability of imported water.

Case Study: Description of Study Area and Proposed Conjunctive-Use Project

Description of Study Area

HDWD has proposed a conjunctive-use project in the Warren subbasin, California. The Warren subbasin is located about 160 km east of Los Angeles in the southwestern part of the Mojave Desert in southern California and is part of the Morongo Groundwater Basin (Figure 1). The areal extent of the Warren subbasin is 48.64 km^2, bounded by the San Bernardino Mountains on the northwest, the Little San Bernardino Mountains on the southwest, both a natural topographic and a groundwater divide on the west, and a series of faults that are referred to as the Yucca barrier on the east (Figure 1). The areal extent of the water-bearing deposits, which is much smaller than that of the subbasin (14.08 km^2 vs. 48.64 km^2), is referred to as the Warren Groundwater

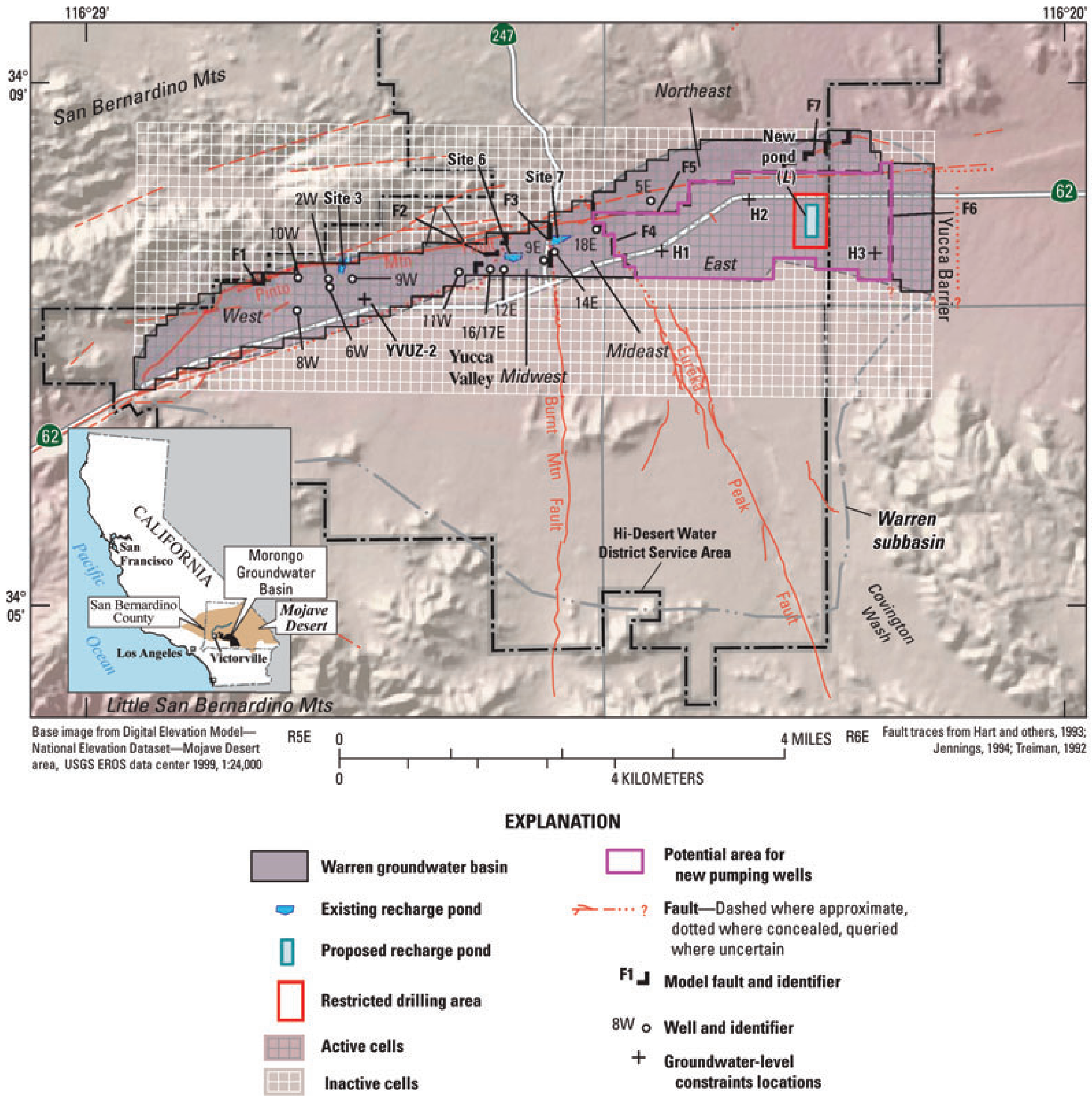

Figure 1. Location of the Warren subbasin, California and model grid for the groundwater flow and transport model.

Basin and is the study area for this paper. Faults separate the groundwater basin into five hydrogeologic units: the west, Midwest, Mideast, east, and northeast hydrogeologic units (Figure 1). The water-bearing deposits in the Warren Groundwater Basin were divided into four aquifers (referred to as the upper, middle, lower, and deep aquifers). The detailed description of geology, hydrogeology, and groundwater development for the study area can be found in Nishikawa et al. (2003).

Nishikawa et al. (2003) developed a 3D groundwater-flow model for the Warren Groundwater Basin based on MODFLOW-2000 (Harbaugh et al. 2000). The spatial discretization of the model consists of three horizontal layers, each divided into a 25 by 75 grid (Figure 1). The grid spacing is about 152.40 m (500 ft) by 152.40 m in the x and y direction, and the model grids cover the entire Warren Groundwater Basin. Three horizontal layers—model layer 1, modeled as an unconfined aquifer, represents the upper and middle aquifers; model layer 2, modeled as a convertible aquifer, represents the lower aquifer; and model layer 3, modeled as a confined aquifer, represents the deep aquifer. All model boundaries are simulated as no-flow boundaries, except the eastern boundary, which is a general-head boundary, and the top boundary (recharge boundary), which is a specified-flux boundary. The faults in the groundwater basin are modeled using the Horizontal-Flow-Barrier package (Hsieh and Freckleton 1993), which simulates faults as thin, vertical, low-permeability geological features that impede horizontal groundwater flow. Evapotranspiration is not simulated because the water table is as deep as 90 m below land surface (bls). The groundwater-flow model was calibrated using measured data from 1956 to 2006 and the year 2006 recharge pattern (natural recharge, septic-tank effluent, and irrigation return flow) used in the model calibration process is repeated for the management models. The simulated groundwater levels at the end of the calibration process were used as the initial conditions for the management model. For specifics regarding the groundwater-flow model see Nishikawa et al. (2003).

Description of Proposed Conjunctive-Use Project

The proposed conjunctive-use project includes a new recharge pond, three existing recharge ponds (Sites 3, 6, and 7), new pumping wells, and 13 existing pumping wells (5E, 9E, 12E, 14E, 16E, 17E, 18E, 2W, 6W, 8W, 9W, 10W, and 11W). The location of the new recharge pond is predetermined by HDWD and located in the east hydrogeologic unit (Figure 1). California State regulations require initially a mixing ratio of 20% reclaimed water to 80% mixing water of nonwaste water origin. In this study, the reclaimed water is the treated waste water from waste water treatment plant and the origin of the nonwaste water is the water pumped from new wells installed according to California State regulations. For the purpose of this study, it is assumed that the mixing water is groundwater pumped from new pumping wells in the east hydrogeologic unit and used as the only source for mixing water. The existing pumping wells are used to satisfy water demand and control groundwater levels. The existing recharge ponds are recharged with imported water only (i.e., no mixing with treated waste water) and are used to recharge the groundwater system. We assume that the new recharge pond and new pumping wells must follow California State regulations, which include: (1) the minimum distance between ponds and wells equals to 152.40 m (500 ft), (2) the minimum travel time (retention time) between ponds and wells equals 6 months, and (3) the mixing ratio of reclaimed water and pumped groundwater should be greater than or equal to 20%. In this proposed project, HDWD wishes to identify the least-cost conjunctive-use strategies that control groundwater levels, meet regulations, meet water-supply demand, and identify the optimal locations of new pumping wells; therefore, the management problem is formulated as a MINLP problem.

Formulation of the Conjunctive-Use Management Problem

The groundwater-management model was formulated as a MINLP problem with the objective of minimizing water-delivery costs subject to constraints on potential new well locations, migration of recharged water, retention time of recharged water, mixing ratio of reclaimed and pumped waters, groundwater levels, water-supply demands, available imported water, and pump/recharge capacities. The formulation can be summarized as:

$$\min J = \left[\sum_{w=1}^{N_W} a_w \cdot \mathrm{CI}_w + \sum_{t=1}^{T} \sum_{w=1}^{N_W} b_{w,t} \cdot (C_{w,t} \cdot Q_{w,t}) + \sum_{t=1}^{T} \sum_{p=1}^{N_P} C_{p,t} \cdot Q_{p,t} + \sum_{t=1}^{T} \sum_{j=1}^{N_J} C_{j,t} \cdot Q_{j,t} \right] \quad (1)$$

subject to

$$d(w, L) \geq d_{\mathrm{r}} \quad (2)$$

$$d(w, L) \geq K_{w,L} \cdot \mathrm{grad}(h_{w,L}) \cdot t_{\mathrm{r}} \quad (3)$$

$$\frac{R}{\sum_{w=1}^{N_W} Q_{w,t} + R} \leq r, t = 1, \ldots, T \quad (4)$$

$$a_w \geq b_{w,t}, a_w \in \{0, 1\}, b_{w,t} \in \{0, 1\}, \quad w = 1, \ldots, N_W, t = 1, \ldots, T \quad (5)$$

$$h_{i,t_c}^{\min} \leq h_{i,t_c} \leq h_{i,t_c}^{\max}, i \subset I, t_c \subset T_c \quad (6)$$

$$\sum_{p=1}^{N_P} Q_{p,t} \geq D_t, t = 1, \ldots, T \quad (7)$$

$$\sum_{j=1}^{N_J} Q_{j,t} \leq A_t, t = 1, \ldots, T \quad (8)$$

$$0 \leq Q_{w,t} \leq Q_w^{\max}, w = 1, \ldots, N_W, \quad t = 1, \ldots, T \quad (9)$$

$$0 \leq Q_{p,t} \leq Q_p^{\max}, p = 1, \ldots, N_P, \quad t = 1, \ldots, T \quad (10)$$

$$0 \leq Q_{j,t} \leq Q_j^{\max}, j = 1, \ldots, N_J, \quad t = 1, \ldots, T \quad (11)$$

where J is the objective function; $Q_{w,t}$ and $Q_{p,t}$ are the pumping rates (L^3/t) during the tth stress period (1 month) at a new pumping well w and an existing pumping well p; and $C_{w,t}$ and $C_{p,t}$ are the corresponding cost coefficients; $Q_{j,t}$ is the recharge rate (L^3/t) during the tth stress period for a recharge pond j with corresponding cost coefficient, $C_{j,t}$; N_W, N_P, and N_J are the number of new pumping wells, existing pumping wells, and recharge ponds, respectively; T is the operation horizon; CI_w is the installation cost, which includes well and pipeline (from the new pumping well to the new recharge pond) construction costs, for new pumping well w; a_w is the binary variable used to represent the installation of the new pumping well w, $a_w = 1$ if the well is installed, otherwise $a_w = 0$; $b_{w,t}$ is the binary variable used to represent the operation during the tth stress period for the new pumping well w, $b_{w,t} = 1$ if the new well w is pumping during the tth stress period, otherwise $b_{w,t} = 0$; and $Q_{w,t}$, $Q_{p,t}$, $Q_{j,t}$, a_w, and b_w are decision variables. The total cost includes the installation of new pumping, which includes well and pipeline construction costs, new and existing pumping-well operations, and recharge pond operations.

Equations 2 to 4 are set according to California State regulations. Equation 2 ensures that the location of a new pumping well satisfies the State distance regulation (i.e., no closer than 152.4 m from the recharge pond). The variable $d(w, L)$ is the distance of new pumping wells (w) from the new recharge pond (L) and d_{r} is the minimum distance defined by the State regulation. Equation 3 ensures that the retention time of the reclaimed water satisfies State regulations. $K_{w,L}$ is the hydraulic conductivity between the new pumping well and the new recharge pond, $\mathrm{grad}(h_{w,L})$ is the hydraulic gradient between the new pumping well (w) and the recharge pond (L), and t_{r} is the minimum travel time defined by the State regulation. Equation 3 is an approximation to the regulation under the assumptions of linearity and steady state. Equation 4 ensures that the State regulation defining the ratio of reclaimed water to pumped groundwater is satisfied. R is the production rate of the reclaimed water and r is the specified ratio of mixing reclaimed and pumped waters. Although the new pumping wells are not used to satisfy the water demand, we assume they are production wells and, therefore, subject to the State regulations.

Equation 5 ensures that a new pumping well will be installed before it can be operated. Equation 6 restricts the maximum/minimum groundwater level at the end of the t_cth stress period at location i; $h_{i,t_c}^{\max}$ is the maximum allowable groundwater level at the end of the t_cth stress period at location i; $h_{i,t_c}^{\min}$ is the minimum required groundwater level at the end of the t_cth stress period at location i; h_{i,t_c} is the simulated groundwater level at the end of the t_cth stress period, at location i; I is the set of groundwater-level constraint locations and T_{c} is the set of constrained stress periods. The maximum required groundwater levels are used to prevent the rising rates of groundwater levels. According to Nishikawa et al. (2003), the rapidly rising groundwater levels resulting from the artificial-recharge program at Sites 6 and 7 entrained septic-tank effluent stored in the unsaturated zone and caused the high-nitrate concentrations in the groundwater. The minimum required groundwater levels are used to prevent over-pumping.

Equation 7 ensures that the water-supply demand is met, and D_t is the water-supply demand during the tth stress period. Equation 8 sets an upper limit on the total amount of the recharge water, and A_t is the total available imported water for recharge during the tth stress period. Equations 9 to 11 limit the new pumping at well w, the existing pumping at well p, and recharge at pond j to be less than or equal to the new pumping capacity of the well, $Q_w^{\max}$, the pumping capacity of the well, $Q_p^{\max}$, and recharge capacity of the pond, $Q_j^{\max}$.

Equations 3 and 6 indicate the dependence of groundwater levels on the pumping rates and are determined using the simulation model. When the aquifer is modeled as unconfined, these two constraints are the sources of nonlinearity.

Conjunctive-Use Management Model

The locations of existing pumping wells, existing recharge ponds, proposed new recharge pond, and potential locations of new pumping wells are shown in Figure 1. Existing recharge sites are located in the west, Midwest, and Mideast hydrogeologic units: Sites 3, 6, and 7, respectively (Figure 1). The cost coefficients, CI_w, $C_{w,t}$, $C_{p,t}$, and $C_{j,t}$, and capacities of wells and ponds, $Q_w^{\max}$, $Q_p^{\max}$, and $Q_j^{\max}$ were supplied by HDWD and its consultant, Montgomery-Watson-Harza (MWH) (Jeffrey Mohr, MWH, personal communication, 2008; Table 1). The installation cost, CI_w, lumps the well and pipeline construction costs together, and are equal to $\$1.00 \times 10^6$/well (Jeffrey Mohr, MWH, personal communication, 2008) and \$328.08/m (=\$100.0/ft) (Gail K. Masutani, PBS&J, personal communication, 2010), respectively. HDWD is allocated 5.28×10^6 m^3/year (4.28×10^3 acre-ft/year, AFY) of imported water from the California State Water Project (SWP) to artificially recharge at Sites 3, 6, and 7 (Joseph Glowitz, HDWD, personal communication, 2009). We assume the annual imported water is evenly distributed over each of the 12 months, so A_t is equal to 4.40×10^5 m^3/month (1.45×10^4 m^3/d). The monthly water-supply demand, D_t, is estimated based on the historical water-supply data provided by HDWD, and is projected to increase 2% per year over a 5-year planning horizon (Joseph Glowitz, HDWD, personal communication, 2009).

Table 1
The Installation Costs of the New Pumping Well and the Unit Costs of the New Pumping Wells, Existing Pumping Wells, and Recharge Ponds in the Groundwater-Management Model

Well Name	Installation Cost ($/well)
Each new pumping well	1,000,000

Well/Pond Name	Capacity (m^3/d)	Unit Cost ($/$m^3$)
Each new pumping well	5678.49	0.05
Water-supply well 5E	855.62	0.08
Water-supply well 9E	1945.58	0.03
Water-supply well 12E	7994.85	0.08
Water-supply well 14E	3585.96	0.03
Water-supply well 16E	1193.50	0.04
Water-supply well 17E	2070.92	0.04
Water-supply well 18E	1465.99	0.08
Water-supply well 2W	523.18	0.11
Water-supply well 6W	2332.51	0.07
Water-supply well 8W	1297.05	0.12
Water-supply well 9W	4561.48	0.06
Water-supply well 10W	1367.90	0.07
Water-supply well 11W	5542.44	0.06
Recharge pond Site 3	6167.41	0.25
Recharge pond Site 6	6167.41	0.25
Recharge pond Site 7	6167.41	0.25

Groundwater-level constraints were specified at well YVUZ-2: well 9E and well 18E; and locations H1, H2, and H3 represent the west, Midwest, Mideast, and east hydrogeologic units, respectively (Figure 1). The groundwater-level constraints are set at the end of each year (every 12 stress periods), and the maximum allowable groundwater levels, $h_i^{\max}$, are set 45.72 m (150 ft) bls for all constraint locations, except wells 9E and 18E (the corresponding groundwater-level constraints are shown in Figure 9A). At the beginning of the simulation, groundwater levels for wells 9E and 18E are less than 45.72 m bls. To maintain feasibility, the maximum allowable groundwater level for well 9E is set at 33.53 m (110 ft) bls at the end of the first year and at 38.10 m (125 ft), 42.67 m (140 ft), 44.20 m (145 ft), and 45.72 m bls at the end of the second, third, fourth, and fifth years, respectively (the corresponding groundwater-level constraints are shown in Figure 9B). The maximum allowable groundwater level for well 18E is set at 14.21 m (46 ft) bls at the end of the first year and at 23.16 m (76 ft), 31.70 m (104 ft), 39.32 m (129 ft), and 45.72 m bls at the end of the second, third, fourth, and fifth years, respectively (the corresponding groundwater-level constraints are shown in Figure 9C). The minimum required groundwater levels, $h_i^{\min}$, are set 45.72 m below $h_i^{\max}$ for all constraint locations (the corresponding groundwater-level constraints are shown in Figure 9A–9C), except well YVUZ-2. The minimum groundwater levels for well YVUZ-2 are required to increase at a rate of 4.57 m/year (15 ft/year) because the initial groundwater level is lower than the predevelopment condition in 1958 (the corresponding groundwater-level constraints are shown in Figure 9D). The increasing rate of 4.57 m/year is needed to maintain feasibility of the management model. If the rate is too large, the optimization problem is infeasible because a combination of the maximum allowable recharge for Site 3 and no pumping for the production wells in the west hydrogeologic unit will not satisfy this constraint.

The production rate of the reclaimed water is equal to 3.79×10^3 m^3/d (1 million gallons per d, MGD); therefore, the total pumping from the new wells should be greater than or equal to 1.51×10^4 m^3/d (4 MGD) to meet the State regulations. HDWD specified that new pumping wells could only be located in the east hydrogeologic unit, referred to as the potential area on Figure 1. The new pumping wells are not allowed within 152.40 m of the new recharge pond (within the rectangular area around the new recharge pond shown in Figure 1) per State regulation; therefore, there are 203 potential new well locations (Figure 1).

Development of a Hybrid-Optimization Algorithm for a MINLP Problem

Genetic Algorithm

A GA is a search technique based on the mechanics of natural selection and natural genetics, and is used to find exact or approximate solutions to optimization and search problems. GAs use a random-search procedure inspired by biological evolution, cross-breeding trial designs and allowing only the fittest designs to survive and propagate to successive generations. The algorithm uses chromosomes to encode the decision variables and starts from a group or a population of chromosomes, in which each decision variable value is initially randomly assigned. In this study, a chromosome represents a set of binary decision variables, which is a set of potential locations for installing the new pumping wells. If the bit in a chromosome equals 1, that location is selected to install a new pumping well. If the bit equals 0, that location is not selected. The length of the chromosome equals to the number of binary decision variables. The population is the set of chromosomes currently involved in the search process, and the population size is the number of chromosomes in population.

At each generation, GAs decode the chromosomes in the population and then evaluates their performance using a fitness function representing the objective function. Three operators—selection, crossover, and mutation—are implemented to improve the fitness function generation by generation (Goldberg 1989). Selection is an operator to select chromosomes from the population to be parents to crossover and mutate. In this study, the tournament selection is used to select the chromosomes as the parents to generate new chromosomes, called offspring. The tournament selection provides selective pressure by holding a tournament competition among k individuals. The best individual from the tournament is the one with the highest fitness and is then inserted into the mating pool for crossover and mutation to generate the offspring. Elitism, the first best chromosome (or the few best chromosomes) is directly copied into the new population as the offspring, is the other selection method used in this study. Crossover is an operator to select chromosomes from parent chromosomes and create a new offspring. The crossover probability (p_c) indicates the expected number of chromosomes ($p_c \times$ population size) that undergo the crossover operation. Mutation is an operator to involve a probability that an arbitrary bit in a chromosome will be changed from its original state, that is, change from 0 to 1 or vice verse. The mutation probability (p_m) indicates that the expected number of mutated bits ($p_m \times$ number of bits in a chromosome $\times$ population size). Every bit (in all chromosomes in the entire population) has an equal chance to undergo mutation. Niching, a method to permit a formation of stable subpopulations of different chromosomes based on sharing, is also used in this study. The detailed review of niche method and GA can be found in Goldberg (1989), Michalewicz (1994), and Sivanandam and Deepa (2008). A large number of GA examples can also be found in these references.

The computational time required to solve an optimization problem using a GA increases with the complexity of the problem. In particular, as the number of decision variables increases, so does the required population size. Large population sizes imply large number of fitness function evaluations. To reduce the computational burden, parallel computing, which decodes and evaluates the fitness of each chromosome on separate processors, is applied in the hybrid-optimization algorithm. In this study, the GA has a population size of 50, the tournament size (k) is 2, the crossover probability is 0.5, and the mutation probability was 0.001. The GA is computed in consecutive generations until the termination criterion, which is heuristic, is met. After testing the GA for our case, the algorithm is ended when the fitness of the optimal chromosome remains constant over 10 generations and the number of generations exceeds a given maximum, 100.

Successive Linear Programming

The SLP algorithm is applied to solve the NLP problem. The SLP is based on repeated linearization of the nonlinear features in the groundwater-management models, and is implemented by recalculating the response matrix for each successive linear program (Louie et al. 1984; Becker and Yeh 1972; Yeh 1992; Ahlfeld and Mulligan 2000). The response matrix consists of the influence coefficients and is used to replace the simulation model in the constraint set of a management model (Becker and Yeh 1972). The influence coefficient is defined as the change in state variable (groundwater levels in this study) for a change in decision variable (pumping/injection rates in this study), evaluated for the set of decision variables, that is,

$$\left.\frac{\partial u_{i,j,k,t}}{\partial Qw_n}\right|_{\mathbf{Qw}} \tag{12}$$

where $u_{i,j,k,t}$ is the groundwater level at location i, j, k and stress period t obtained when the set of decision variables, $\mathbf{Qw}$, is applied; and Qw_n is the nth decision variable.

If the aquifer is modeled as unconfined, the groundwater-level responses to the decision variable may be nonlinear and the response matrix may no longer be constant. Therefore, SLP recalculates the response matrix at each iteration. This recalculation uses the value of the decision variables obtained at previous iteration. The response matrix is updated until two convergence criteria are met: (1) convergence of the infinity norm of the difference between the current and prior decision variables (Equation 13) and (2) convergence of values of the objective function (Equation 14) (Ahlfeld et al. 2005).

$$\|\mathbf{Q}_\mathbf{w}^{\mathbf{v}+1} - \mathbf{Q}_\mathbf{w}^{\mathbf{v}}\|_\infty \leq \varepsilon_1(1 + \|\mathbf{Q}_\mathbf{w}^{\mathbf{v}+1}\|_\infty) \tag{13}$$

$$|J^{v+1} - J^v| \leq \varepsilon_2(1 + |J^{v+1}|) \tag{14}$$

where $\|\|_\infty$ is the infinity norm, which equals max $(|Q_{w1}|, \ldots, |Q_{wn}|)$; $\mathbf{Q}_\mathbf{w}^{\mathbf{v}+1}$ and $\mathbf{Q}_\mathbf{w}^{\mathbf{v}}$ are the set of decision variables at iteration $v+1$ and v; ε_1 is the specified fraction of the decision variable; J^{v+1} and J^v are the objective value at iteration $v+1$ and v, respectively; and ε_2 is the specified fraction of the objective value. ε_1 and ε_2 are equal to 10^{-4} and 10^{-3} in this study.

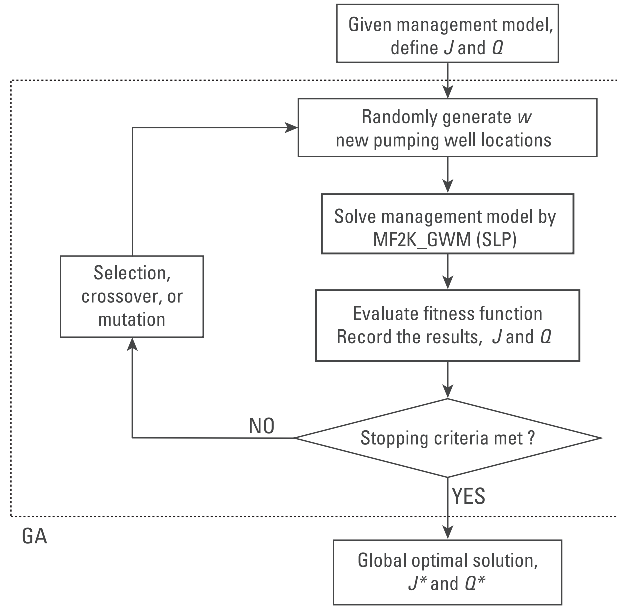

Figure 2. Flowchart for the hybrid-optimization algorithm.

Hybrid-Optimization Algorithm

Figure 2 shows the flowchart of the proposed hybrid-optimization algorithm for solving MINLP problems. The GA does not require calculating the derivatives of state variables relative to decision variables; therefore, addressing the discontinuity in the decision variables is straightforward. First, the GA randomly generates chromosomes where each chromosome represents a set of new pumping-well locations. Given each chromosome, the MINLP problem becomes a NLP problem that is solved by the SLP algorithm to obtain the optimal pumping/recharge rates. The optimal objective value obtained from the SLP algorithm is the fitness function value used by the GA. The GA produces subsequent generations applying the three operators (selection, crossover, and mutation) to the current generation. The SLP algorithm then solves the optimization problem defined by the new generation of chromosomes. The SLP results are then returned to the GA to evaluate the fitness function; with the cycle continuing until the convergence criteria are met. The GA program developed by D. L. Carroll (FORTRAN genetic algorithm driver, version 1.7a, 2001, available at http://cuaerospace.com/carroll/ga.html) is modified to serve our purpose and MF2K_GWM (Ahlfeld et al. 2005), which applies the SLP algorithm to solve the NLP, also is modified and embedded into the GA.

Testing the Hybrid-Optimization Algorithm for the Simplified Case Study

To test the hybrid-optimization algorithm, the algorithm was used to solve a simplified version of the case study and the results were compared with the results obtained using the enumeration-search method, branch-and-bound method, and GA. The enumeration-search method examines the entire solution domain and the

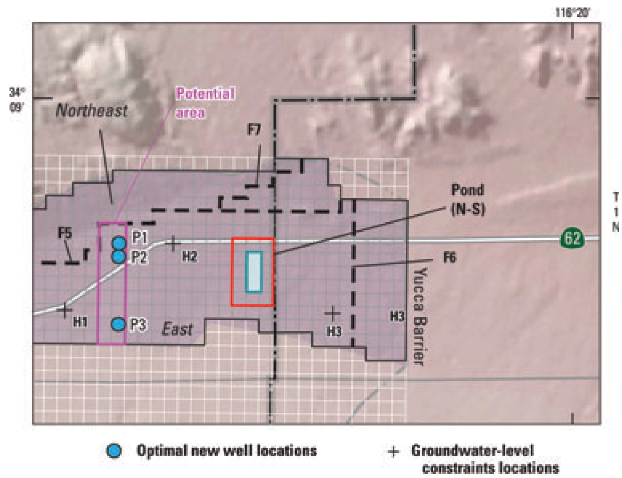

Figure 3. Results of testing the hybrid-optimization algorithm for the simplified case study.

identification of the global optimum is guaranteed (Jajszczyk and Wojcik 2005; Jech 2006). The branch-and-bound method is an optimization algorithm, which uses splitting and bounding procedures to treat the MINLP problem as several NLP subproblems (Rardin 1998). To make the enumeration-search method tractable, the potential new well locations were restricted to a small area (Figure 3), referred to as the simplified version of the case study, and the number of potential well locations was reduced from 203 to 18.

The optimal results are shown in Table 2. All the methods, except GA, identified the same three new pumping well locations and the minimum objective values are also the same, $\$8.46 \times 10^6$. GA did not converge to the global optimal solution after 72.0 h of CPU time. These results indicate that the hybrid-optimization algorithm can identify the global optimum solution for a MINLP problem. Compared to the enumeration method, the branch-and-bound method and hybrid-optimization algorithm reduce the computation time by about 96 and 82%, respectively. These results imply that the branch-and-bound method is the most efficient approach in terms of the computation time to solve this simplified case study. However, this conclusion is only valid for a small number of binary decision variables. When the number of binary decision variables is large, the branch-and-bound method becomes less efficient and the global optimum is not guaranteed. This will be discussed further in the next section.

Utilizing the Hybrid-Optimization Algorithm for the Case Study

The algorithm is now used to solve the groundwater-management problem (Equations 1–11) with 203 potential new well locations (Figure 1). Table 3 summarizes the configuration for the case study; referred to as the base case, and sensitivity analysis alternatives 1, 2, and 3, which are discussed in Section "Sensitivity Analysis."

The algorithm converged after 42 generations (Figure 4). Three new pumping wells were required and the algorithm identified the locations of the new pumping wells: P1, P2, and P3 (Figure 5). All three new pumping wells are active during the 5-year management

Table 3
Orientation of the New Recharge Ponds, Mixing Ratio of Reclaimed Water and Pumped Groundwater; and the Percentage of Imported Water Supply Simulated in the Base Case and Sensitivity Analysis Alternatives 1–3 of the Groundwater-Management Model

Simulation	New Recharge Pond Orientation	Mixing Ratio (%)	Percentage of Imported Water Supply
Base Case	North-south	20	100% supply
Alternative 1	East-west	20	100% supply
Alternative 2A	North-south	0	100% supply
Alternative 2B	North-south	50	100% supply
Alternative 3A	North-south	20	50% for years 4 and 5
Alternative 3B	North-south	20	0% for years 4 and 5

Table 2
Results of the Enumeration-Search Method, Branch-and-Bound Method, Genetic Algorithm, and Hybrid-Optimization Algorithm for the Simplified Case Study

Optimization Algorithm	Enumeration	Branch-and-Bound	Genetic Algorithm	Hybrid
Objective value ($\$, \times 10^6$)	8.46	8.46	8.83	8.46
Well location P1	(7, 54)	(7, 54)	(7, 54)	(7, 54)
Well location P2	(8, 54)	(8, 54)	(8, 53)	(8, 54)
Well location P3	(13, 54)	(13, 54)	(13, 54)	(13, 54)
CPU time (h)[1]	68.9	3.1	72.0[2]	12.4

[1]2.6 GHz AMD Opteron CPU and 2 GB RAM.
[2]Did not converge.

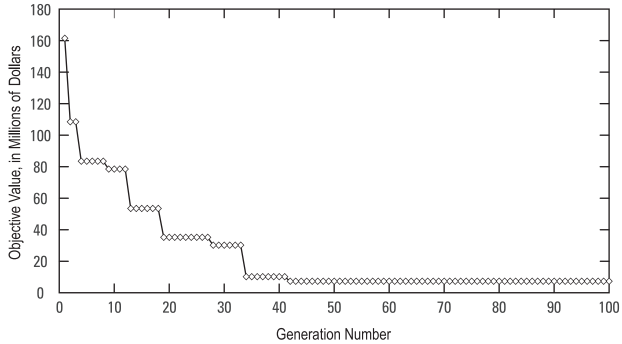

Figure 4. Objective-function convergence for the base case.

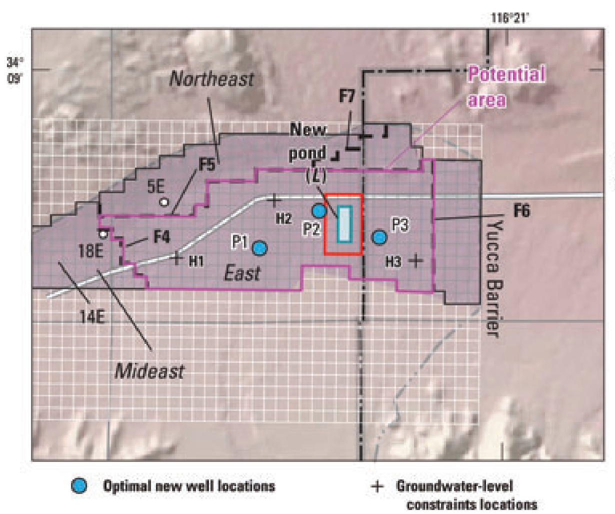

Figure 5. Optimal new well locations for the base case.

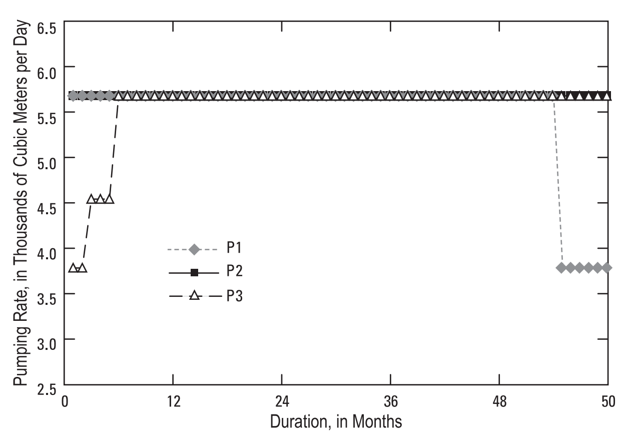

Figure 6. Optimal pumping schedules for new pumping wells for the base case.

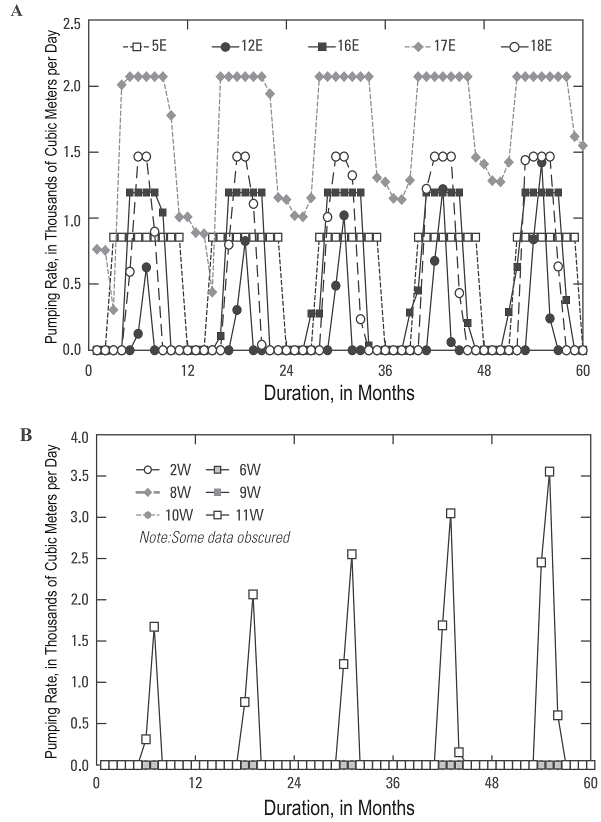

Figure 7. Optimal pumping schedules for the existing pumping wells for the base case; (A) wells 5E, 12E, 16E, 17E, and 18E; and (B) wells 2W, 6W, 8W, 9W, 10W, and 11W.

horizon. Well P1 pumps at its maximum capacity from the beginning to the 54th month, well P2 pumps at its maximum capacity for the entire management horizon, and well P3 pumps at its maximum capacity from the sixth month to the end of the management horizon (Figure 6).

The optimal pumping schedules for the existing pumping wells are shown in Figure 7A, 7B. Wells 9E and 14E, located in the Midwest and Mideast hydrogeologic units, respectively, pump at their maximum capacities for the entire management horizon. These wells can be interpreted as the base producers and they supply more than 60% of the water demand (a total of 1.01×10^7 m^3 from 1.64×10^7 m^3). The reason these wells are pumping at their maximum capacities is that the initial groundwater levels at constraint locations 9E and 18E are much higher than the maximum allowable groundwater level, 45.72 m bls. Consequently, these wells pump at their maximum capacities to decrease the groundwater level at these locations. The optimized pumping schedules for the wells 5E, 12E, 16E, 17E, and 18E vary with the water-supply demand, which is higher during the summer season and lower during the winter season (Figure 7A). These wells can be interpreted as the seasonal producers to supply seasonally varied water demand. Well 14E operates at its maximum capacity to decrease the groundwater level at location 18E, instead of well 18E itself, is due to 14E's cheaper unit price of pumping (0.03 vs. 0.08 \$/m^3). The optimal solution tends to activate the pumping wells, which cost less to operate in order to minimize the objective function. Wells in the west hydrogeologic unit are inactive with the exception of well 11W, which is used to meet the increasing water-supply demand (Figure 7B).

The optimal recharge schedules for Sites 3, 6, and 7 are shown in Figure 8. The recharge rate of Sites 6 and 7 is equal to 0 during the entire planning horizon. Site 3 is the

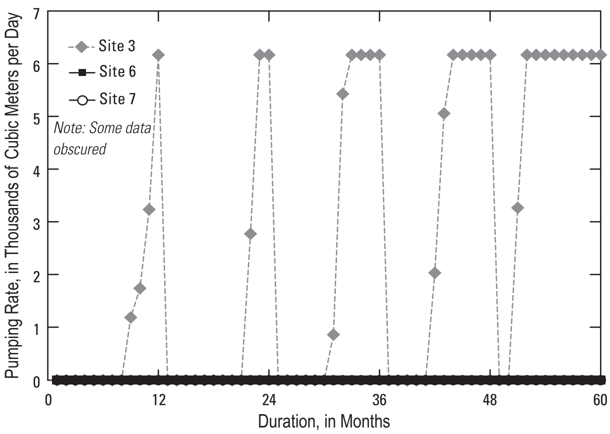

Figure 8. Optimal recharge schedules at Sites 3, 6, and 7 for the base case.

only recharge pond to operate and reaches its maximum recharge capacity during some months. The reason why Site 3 is active is because the groundwater level at well YVUZ-2 is constrained to increase 4.57 m/year (15 ft/year). The simulated hydrographs at wells YVUZ-2, 9E, 18E, and H3 are shown in Figure 9A–9D. In these figures, we see that all groundwater-level constraints are satisfied, and some of them are binding or near-binding, such as the lower bounds for well YVUZ-2 (Figure 9A), the upper bounds for well 18E (Figure 9C), and the last upper bound for location H3 (Figure 9D). The optimized pumping and recharge strategy can effectively control the groundwater levels while minimizing the operational cost.

The minimum total objective value is equal to $\$7.26 \times 10^6$. The installation cost for new wells, the pumping cost for new and existing wells, and the recharge cost for imported water are listed in Table 4. From Table 4, we see that the installation cost for the three new wells is equal to $\$3.80 \times 10^6$, which accounts for more than half of the total cost. If we subtract the installation cost from the total cost, we find that the pumping cost for new wells, the pumping cost for existing wells, and the artificial-recharge costs are 46.9, 19.3, and 33.8%, respectively. The pumping cost for existing wells ($\$6.68 \times 10^5$), is relatively inexpensive because the average unit cost of pumping is less expensive compared to the unit costs of imported water and new pumping wells (Table 1).

To compare the efficiency of the branch-and-bound method, GA, and the hybrid-optimization algorithm for the case with a large number of binary decision variables, the three methods were applied to solve the base case, which has 203 binary decision variables. The results are shown in Table 5. The hybrid-optimization algorithm required 52.5 h of CPU time to identify the optimal solution; however, both branch-and-bound method and

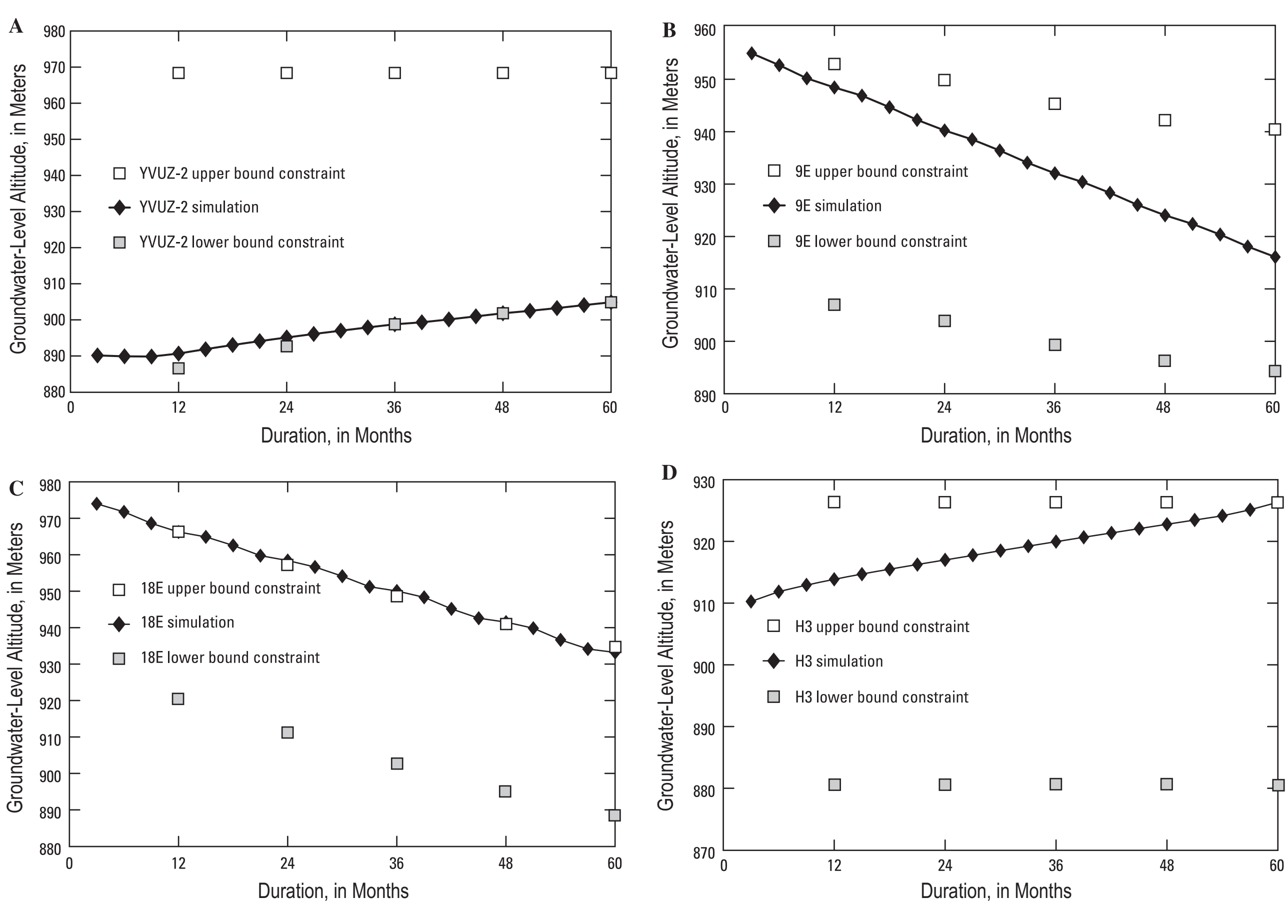

Figure 9. Simulated hydrographs at (A) well YVUZ-2, (B) well 9E, (C) well 18E, and (D) location H3 for the base case.

Table 4
Results of the Base Case and Sensitivity Analysis Alternatives 1–3 of the Simulated Groundwater-Management Model

		Sensitivity Analysis Alternatives				
Simulation	**Base Case**	**1**	**2A**	**2B**	**3A**	**3B**
New well construction cost ($\times 10^6$, \$)	3.00	3.00	0.00	1.00	3.00	3.00
New well pipeline cost ($\times 10^6$, \$)	0.80	1.15	0.00	0.100	0.85	0.90
New well pumping cost ($\times 10^6$, \$)	1.62	1.64	0.00	0.55	1.62	1.62
Water supply well pumping cost ($\times 10^5$, \$)	6.68	6.70	6.68	6.68	6.68	6.69
Imported water cost ($\times 10^6$, \$)	1.17	1.20	1.143	1.15	1.41	1.67
Total objective value ($\times 10^6$, \$)	7.26	7.66	1.811	3.47	7.55	7.86
Well location P1	(11, 57)	(10, 53)		(9, 66)	(11, 57)	(11, 57)
Well location P2	(8, 62)	(10, 58)			(8, 62)	(8, 62)
Well location P3	(10, 67)	(10, 69)			(10, 68)	(11, 68)

Table 5
The Comparison of the Branch-and-Bound Method, Genetic Algorithm, and Hybrid-Optimization Algorithm for the Base Case Study

	Branch-and-Bound	**Genetic Algorithm**	**Hybrid**
Objective value (\$, $\times 10^6$)	7.70	8.04	7.26
Well location P1	(9, 52)	(11, 53)	(11, 57)
Well location P2	(7, 60)	(7, 68)	(8, 62)
Well location P3	(11, 68)	(11, 67)	(10, 67)
CPU time (h)[1]	72.0[2]	72.0[2]	52.5

[1]2.6 GHz AMD Opteron CPU and 2 GB RAM.
[2]Did not converge.

GA could not converge to the optimal solution after 72.0 h of CPU time. Based on this case, we can conclude that when the number of binary decision variables is large, the hybrid-optimization algorithm is more efficient than the branch-and-bound method and the GA.

It should be noted that the potential issue of nonuniqueness of the solution could exist in this conjunctive-use management problems. Due to the setting of the convergence criteria, in both GA and SLP, the global optimum is not guaranteed and the unique global optimum may not be identified. The iterative nature of the GA and SLP results in identifying a local optimum. Theoretically, the global optimum can be identified as long as the hybrid-optimization algorithm can be run for a long enough period. The nonuniqueness of the solution can be addressed by running the hybrid-optimization algorithm using many different initial guesses and comparing the results. However, there are 2^{203} different initial guesses in our particular case and it is infeasible to test all of them. It should also be noted that nonuniqueness could also arise from the parameter uncertainties introduced by the model calibration. Parameter variability can produce different management solutions and may have an impact on management policies (Loaiciga and Marino 1987). However, a complete analysis of parameter uncertainty is beyond the scope of this paper.

Sensitivity Analysis

A sensitivity analysis was performed to test the sensitivity of the groundwater-management model to changes in the orientation of the new recharge pond, the mixing ratio of the reclaimed water and pumped groundwater, and the quantity of imported water supply. Specifically, the three alternatives were (1) changing the orientation of the new recharge pond from north-south to east-west; (2) changing the ratio of reclaimed water to pumped groundwater from 20 to 0 and 50%; and (3) reducing the quantity of available imported water supply by 50 and 100% in years 4 and 5 (Table 3).

New Recharge Pond Orientation (Alternative 1)

In Alternative 1, the new recharge pond layout is changed from a north-south orientation to an east-west orientation, and the remainder of the constraint sets is unchanged with the exception of the potential locations of the new pumping wells. The prohibited area, (e.g., 152.40 m between new pumping wells and the new recharge pond) is changed to correspond to the new recharge pond layout (Figure 10A).

The hybrid-optimization algorithm required 50 generations to converge. The optimal locations of new wells P1, P2, and P3 are shown in Figure 10A. The optimized pumping schedules for the new and existing pumping wells and optimized recharge schedules are very similar to the base case.

The minimum total objective value is equal to \$7.66 $\times 10^6$ (Table 4). The pumping cost for new and existing wells (\$1.64 $\times 10^6$ and \$6.70 $\times 10^5$, respectively), and recharge cost (\$1.20 $\times 10^6$) are slightly higher than the costs obtained from the base case (Table 4) indicating that the north-south orientation may be preferable

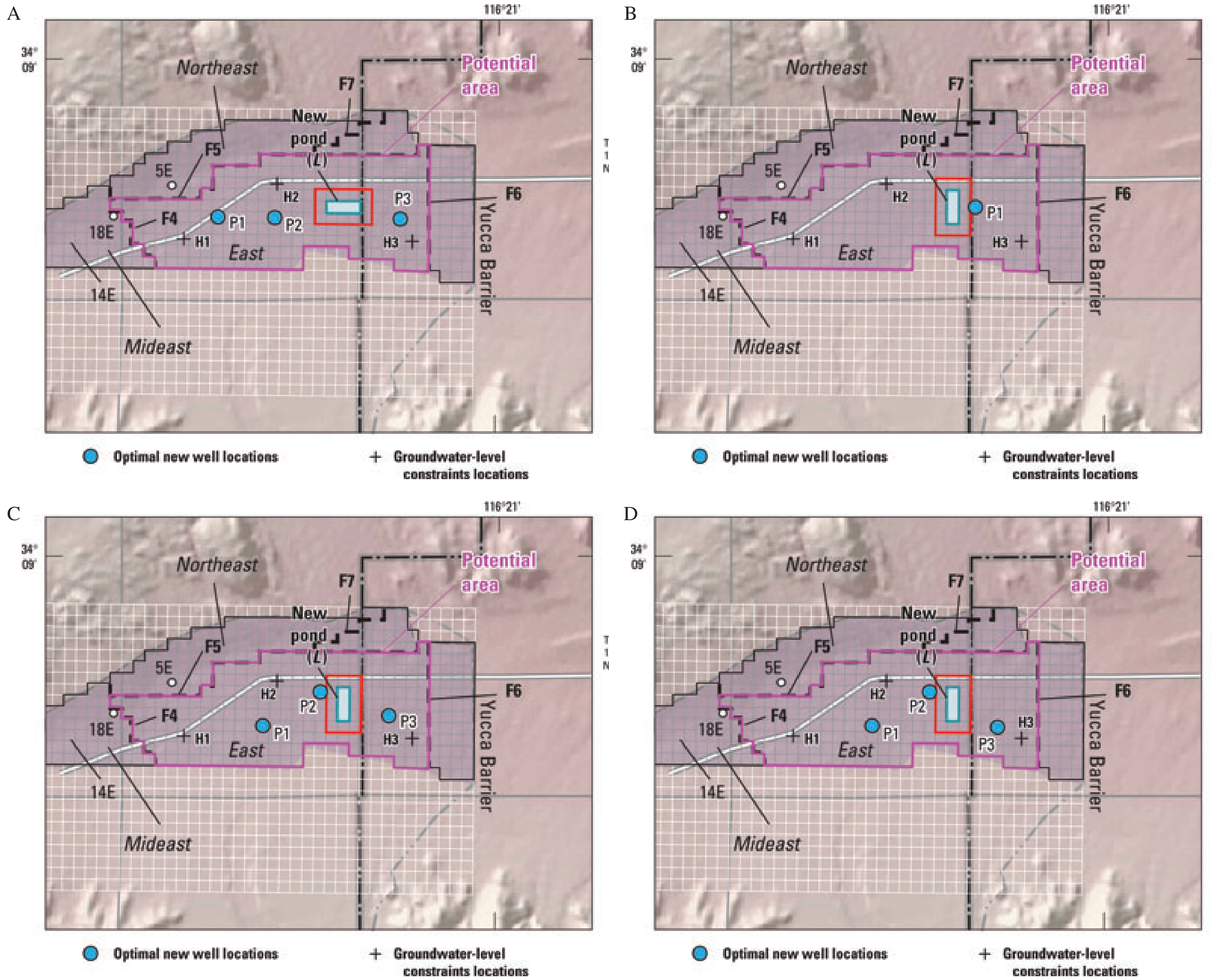

Figure 10. Optimal new well locations for the (A) Alternative 1, (B) Alternative 2B, (C) Alternative 3A, and (D) Alternative 3B.

to the east-west orientation. The results also indicate that the new pumping well locations are sensitive to the new recharge pond orientation; however, the optimal pumping/recharge schedules are not.

Different Mixing Ratios of Reclaimed Water and Pumped Groundwater (Alternative 2)

In Alternative 2, two different mixing ratios of reclaimed water and pumped groundwater were tested: (1) 0% mixing ratio, referred to as Alternative 2A, that is, 3.79×10^3 m^3/d of reclaimed water and no pumped groundwater and (2) a 50% mixing ratio, referred to as Alternative 2B, that is, 3.79×10^3 m^3/d of reclaimed water mixed with an equal volume of pumped groundwater (Table 3). In this Alternative, we are demonstrating the solution's sensitivity to different mixing ratios and are not implying any kind of regulatory flexibility.

For Alternative 2A, the optimal solution indicates that no new pumping wells are needed. No new pumping well is needed because the recharge rate of the new recharge pond is so low that the groundwater levels around the new recharge pond will not rise above 45.72 m bls within the planning horizon. The pumping schedules of the existing wells and recharge schedules are very similar to the base case.

The minimum total objective value is equal to $\$1.81 \times 10^6$ (Table 4). The pumping cost for existing wells ($\$6.68 \times 10^5$) and recharge cost ($\$1.14 \times 10^6$) are very close to the base-case values (Table 4).

For Alternative 2B, the algorithm converged after 29 generations and the optimal solution indicates that one new pumping well, P1, is required (Figure 10B). Only one new pumping well is needed because 3.79×10^3 m^3/d of pumped groundwater satisfies the 50% mixing ratio constraint. The pumping schedules of the existing wells and recharge schedules are also similar to the base case.

The minimum total objective value is equal to $\$3.47 \times 10^6$ (Table 4). The pumping cost for the new well is equal to $\$5.50 \times 10^5$. The pumping cost for existing wells ($\$6.68 \times 10^5$) and recharge cost ($\$1.15 \times 10^6$) are also very close to the base-case values (Table 4). According to this analysis, the mixing ratio only affects the number of new pumping wells.

Different Reductions in the Imported Water Supply in Years 4 and 5 (Alternative 3)

In Alternative 3, two different reductions in the imported water supply in years 4 and 5 were tested. We assume that HDWD receives its full allocation of SWP water for the first 3 years, and (1) 50% of its allocation in years 4 and 5, referred to as Alternative 3A, and (2) 0% of its allocation in years 4 and 5, referred to as Alternative 3B (Table 3).

For Alternative 3A, the optimization algorithm required 56 generations to converge. The optimal locations of new wells P1, P2, and P3 are shown in Figure 10C. Compared to the base case, the optimal locations of the new wells are almost the same except for well P3, which is shifted one column to the east (Figure 10C). The optimal pumping schedules for the new pumping wells in this case are very similar to the base case.

The optimized pumping schedules for the existing wells in this case are similar to the base case, except for wells 11W and 12E. To meet the groundwater-level constraint at well YVUZ-2, which is constrained to increase 4.57 m/year, the pumping rate of well 11W decreases to 0 after the third year, and the pumping rate of well 12E increases to compensate for the deficit of water-supply demand caused by decreased pumping at well 11W. The Site 3 recharge schedule in this case is also significantly different from the base case. The recharge rate at Site 3 reaches its maximum recharge capacity from month 11 to 12, 21 to 24, and 29 to 36. After month 36, recharge is reduced to 50% and remains constant until month 60 (Figure 11A).

The minimum total objective value is equal to $\$7.55 \times 10^6$ which is greater than the base-case objective value (Table 4). The objective value for this analysis is much higher than the base-case value because the total volume of artificial recharge at Site 3 is greater than the total volume recharged at Site 3 in the base case (5.71×10^6 vs. 4.72×10^6 m^3). Another reason for the higher objective value is that the pipeline cost for three new wells in this case is slightly higher than the costs in the base case (Table 4). The pumping cost for existing wells is about equal to the cost of the base case (Table 4). The results from this analysis indicate that the pumping/recharge schedules in the west hydrogeologic unit are sensitive to the changes in the supply of SWP water; however, the new well locations and their schedules are insensitive to changes in the supply of SWP water.

For Alternative 3B, the optimization algorithm required 46 generations to converge. The optimal locations of new wells P1, P2, and P3 are shown in Figure 10D, which are the same as Alternative 3A, except for well P3, which is shifted one row to the south. The optimal pumping/recharge schedules are similar to Alternative 3A, except for wells 11W and 12E. Well 11W is inactive during the entire planning horizon and the well 12E pumps more groundwater to compensate for the deficit of water-supply demand caused by the lack of pumping at well 11W. The Site 3 recharge rate equals its maximum recharge capacity from month one to month 36. After month 36, the recharge rate is equal to zero (the maximum available imported water is reduced to 0 after month 36; Figure 11B).

The minimum total objective value is equal to $\$7.86 \times 10^6$ (Table 4). The objective value is greater than the value in Alternative 3A because the west hydrogeologic unit receives an even larger volume of recharge water than the volume in Alternative 3A (6.76×10^6 vs. 5.71×10^6 m^3). The pipeline and pumping cost for three new wells, and pumping cost for existing wells are slightly higher than the cost in Alternative 3A (Table 4). Again, the pumping/recharge schedules in the west hydrogeologic unit are sensitive to the changes in the supply of SWP water; however, the new well locations and their pumping schedules are insensitive to changes in the supply of SWP water.

Conclusions

In this paper, a hybrid-optimization algorithm, that couples aGA with SLP, was developed to solve the MINLP

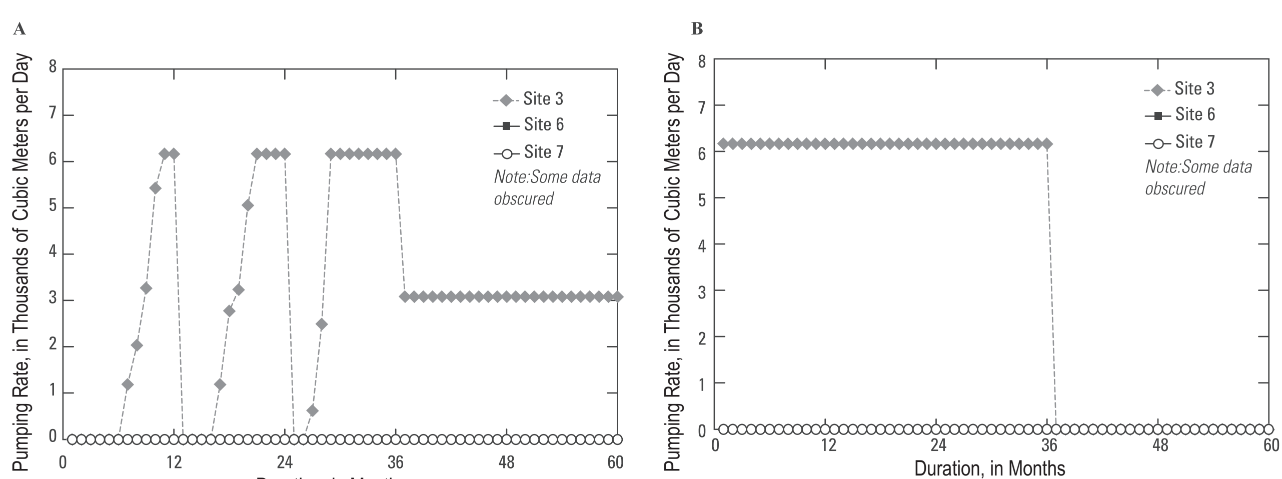

Figure 11. Optimal recharge schedules at Sites 3, 6, and 7 for (A) Alternative 3A, and (B) Alternative 3B.

problem and applied to a groundwater-management problem in the Warren groundwater basin, California. The groundwater-management problem considered conjunctive-use of surface water, reclaimed water, and groundwater. The objective was to minimize water-delivery costs subject to constraints including potential new-well locations, state regulations, groundwater-level constraints, water-supply demand, available imported water, and pump/recharge capacities. As formulated, the decision variables were the time-varying pumping and recharge rates, and optimal locations of the new pumping wells. The GA was used to solve the integer problem and SLP was used to address the nonlinear programming problem.

The hybrid-optimization algorithm was tested by comparing with the enumeration-search and branch-and-bound methods on a simplified version of the groundwater-management problem for the Warren groundwater basin. The optimized results showed that the hybrid-optimization algorithm can find the global optimum, and it could save around 82% of computation time compared to the enumeration method. After the hybrid-optimization algorithm was tested, it was applied to evaluate the groundwater-management problem with 203 potential new well locations. As demonstrated here, the algorithm can be used to effectively solve a real conjunctive-use groundwater-management problem.

In the base case study, the optimized results indicated that the installation cost for the three new wells account for more than half of the total cost. If the installation cost is subtracted from the total cost, the pumping cost for the new wells, the pumping cost for the existing wells, and the recharge cost for the recharge pond account for 46.9, 19.3, and 33.8% of the balance, respectively. The pumping cost for existing wells is relatively inexpensive because the average unit cost of pumping is less expensive compared to the unit costs of imported water and new pumping wells. The optimized pumping schedules for the wells 5E, 12E, 16E, 17E, and 18E vary with the water-supply demand. Wells 9E and 14E pumped at their maximum capacity to decrease the groundwater level for the entire management horizon. Wells in the west hydrogeologic unit are inactive with the exception of well 11W, which is used to meet water-supply demand. Site 3 is the only recharge pond to operate and reaches its maximum recharge capacity during some months because the groundwater level at well YVUZ-2 is constrained to increase 4.57 m/year.

A sensitivity analysis was performed on the groundwater-management problem. The analysis showed that the locations of the new pumping wells were sensitive to the new recharge pond orientation, and a north-south orientation may be preferable to an east-west orientation in terms of the monetary cost. The mixing ratio of reclaimed water and pumped groundwater only affected the number of new pumping wells. The pumping and recharge schedules were sensitive to the quantity of imported water available in years 4 and 5. Reducing the quantity of imported water supply in years 4 and 5 resulted in much higher objective values because of greater recharge in the west hydrogeologic unit. This conjunctive management model can provide the Warren subbasin water managers with information that will improve their ability to manage their surface water, groundwater, and reclaimed water resources.

Acknowledgments

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